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Information technology and innovation outcomes: is knowledge recombination the missing link?

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ABSTRACT

Firms' use of information technology (IT) has been suggested to be an important enabler of knowledge production, leading to innovation outcomes in the form of patent inventions. However the innovation process through which IT use influences patent inventions is largely unclear. We draw on the knowledge recombination perspective and develop a model that explains the innovation process through which IT use influences innovation outcomes by looking into a firm's efforts to recombine existing knowledge (i.e., knowledge recombinant intensity) and the scope of knowledge that is recombined by a firm (i.e., knowledge recombinant diversity). We also distinguish innovation outcomes in terms of patent quantity and quality. Using a large-scale panel dataset, we show that IT use has a stronger impact on knowledge recombinant intensity relative to knowledge recombinant diversity. Moreover, knowledge recombinant intensity and knowledge recombinant diversity play key mediating roles in the relationships between IT use and patent inventions. The impact of IT use on patent quantity is partially mediated, while the impact of IT use on patent quality is fully mediated. Our findings indicate that while IT use can directly affect patent quantity, its impact on patent quality must be channelled through a firm's knowledge recombinant efforts and scope.

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1. Introduction

Information technology (IT) is an organizational resource enabling knowledge production, leading to innovation outcomes in the form of patent inventions (Kleis, Chwelos, Ramirez, & Cockburn, 2012; Nambisan, Lyytinen, Majchrzak, & Song, 2017). In the IS literature, firms' use of IT has been found to be a key enabler of performance outcomes (Devaraj & Kohli, 2003) and, more recently, innovation outcomes such as patent inventions (e.g., Gómez, Salazar, & Vargas, 2017; Joshi, Chi, Datta, & Han, 2010; Kleis et al., 2012; Ravichandran, Han, & Mithas, 2017; Saldanha, Mithas, & Krishnan, 2017; Xue, Ray, & Sambamurthy, 2012). Prior studies linking IT and innovation outcomes have examined the direct link between IT use and patent inventions without providing much insight into the innovation process through which this link is established. This lack of insight is a critical gap in our understanding of IT's role in innovation, since the innovation process between IT use and innovation outcomes has not been systematically theorized nor empirically examined. In other words, the IT-enabled innovation process in knowledge production was assumed to be a black box in past research (e.g., Figure 1 in Kleis et al., 2012, p. 47). Therefore, deepening our understanding of the innovation process through which IT is used for generating patent inventions can provide valuable implications for developing a better digital innovation strategy (Nambisan et al., 2017; Yoo, Henfridsson, & Lyytinen, 2010).

To open up the black box of the innovation process through which IT use influences patent inventions, we draw on the knowledge recombination perspective to explain a firm's innovation process (e.g., Fleming, 2001; Katila & Ahuja, 2002; Rosenkopf & Nerkar, 2001; Wang, Choi, Wan, & Dong, 2016). This powerful theoretical lens has been widely used in the innovation literature and suggests that a patent can be viewed as a recombination of existing knowledge components documented in prior patents (Gruber, Harhoff, & Hoisl, 2012; Nerkar & Paruchuri, 2005). Accordingly, we characterize the innovation process of generating patent inventions by a firm's recombination efforts and by the scope of knowledge that is recombined. Specifically, we theorize *knowledge recombinant intensity* as the average amount of existing knowledge that a firm recombines to create a new patent and *knowledge recombinant diversity* as the average degree to which a firm recombines existing knowledge from different domains to create a new patent. We develop a research model that proposes IT use to be a key enabler to increase a firm's knowledge recombinant intensity and diversity, which, in turn, influences its patent inventions.

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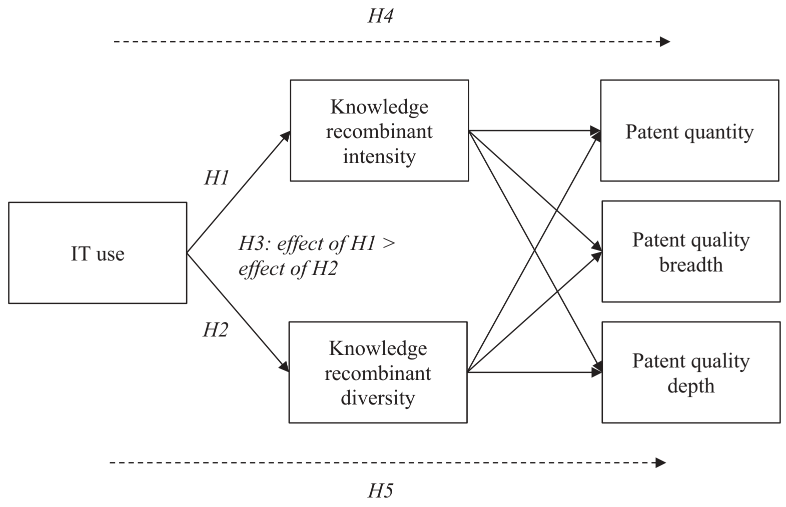

Figure 1. Research Model.

We collect a large-scale panel dataset from 4095 firm-year observations between 2001 and 2003. Empirical results corroborate our theory and provide new insight into the complex innovation process in which knowledge recombinant intensity and knowledge recombinant diversity play key mediating roles in the relationships between IT use and patent inventions. We find that IT use has a stronger impact on knowledge recombinant intensity compared to the impact of IT use on knowledge recombinant diversity. Moreover, the effect of IT use on patent quantity is partially mediated by knowledge recombinant intensity and diversity, while the effect of IT use on patent quality is fully mediated by knowledge recombinant intensity and diversity. Our study has several strengths in terms of the rigour of the empirical work. We adopt a longitudinal design with panel data that allow us to provide more convincing evidence on causality. In addition, we construct a large-scale panel dataset from thousands of firms across several industries, allowing good generalizability of our findings.

Our research makes two major contributions to the digital innovation literature. First, by introducing the knowledge recombination perspective to IS research, we open up the black box of the innovation process through which IT use leads to patent inventions by characterizing this process in terms of a firm's knowledge recombinant intensity and knowledge recombinant diversity. IT use provides stronger support for knowledge recombinant intensity relative to knowledge recombinant diversity and, more importantly, both knowledge recombinant intensity and diversity mediate the impacts of IT use on patent inventions. Second, we enrich the digital innovation literature by explicitly distinguishing and simultaneously considering patent quantity and different aspects of patent quality in our research. We find that the nuanced roles of knowledge recombinant intensity and diversity partially mediate the effect of IT use on patent quantity and fully mediate the effect of IT use on patent quality. Overall, our findings indicate that while IT use can also directly affect patent quantity, its impact on patent quality in terms of both breadth and depth must be channelled by knowledge recombinant efforts and scope.

The rest of the paper is organized as follows. In the next section, we present our theoretical framework and hypotheses. We then describe our methodology and report empirical results. Finally, we conclude by discussing the theoretical contributions, managerial implications, and limitations of this study.

2. Theory and hypotheses

2.1. Patent invention as knowledge recombination

Innovation studies have widely employed the knowledge recombination perspective to explain how a patent is created, postulating that the creation of an invention is essentially due to the recombination of existing knowledge components. Nelson and Winter (1982) stated that any innovation relies to a substantial degree on the recombination of previously existing knowledge. Likewise, a number of studies have pointed out that a patent can be viewed as a combination of existing knowledge documented in prior patents (e.g., Carnabuci & Operti, 2013; Fleming, 2001; Gruber et al., 2012; Katila & Ahuja, 2002; Nerkar & Paruchuri, 2005; Phene, Fladmoe-Lindquist, & Marsh, 2006; Rosenkopf & Nerkar, 2001; Wang et al., 2016). The innovation process of generating patent inventions is essentially a process of knowledge recombination that transfers old ideas to new contexts, leading to "recombinant innovation" (Hargadon & Sutton, 1997).

We conceptualize a firm's innovation process for knowledge recombination based on two key characteristics: the efforts invested in recombining knowledge and the scope of knowledge that is recombined. In a knowledge recombination process, the firm needs to deploy organizational resources (e.g., IT and R&D investments; R&D investment is controlled in this study) to exert efforts to support this process. Moreover, the scope of knowledge that is used for recombination has been found to be critical for the success of recombination (Fleming, 2001) because it determines the richness of knowledge inputs and thereby the innovation outcomes. Accordingly, we define *knowledge recombinant intensity* as the average amount of existing knowledge that a firm recombines to create a new patent and *knowledge recombinant diversity* as the average degree to which a firm recombines existing knowledge from different domains to create a new patent. We develop a model proposing IT use as a key enabler that facilitates knowledge recombinant intensity and diversity, which, in turn, influence innovation outcomes in the form of patent inventions.

For innovation outcomes, we consider both the quantity and quality of patent inventions. We define *patent quantity* as the number of patents that a firm creates. Since patent quality in various future applications can indicate its value (Rosenkopf & Nerkar, 2001; Valentini, 2012), we consider the breadth and depth of a patent's impact on future patent inventions as manifested in the forward citations received by the patent. We define *patent quality breadth* as the degree to which a firm's patents have widespread citations from subsequent patents across different domains. Furthermore, we define *patent quality depth* as the average number of citations that a firm's patents receive from subsequent patents. In this study, we develop a model that characterizes the innovation process through which IT useinfluences patent inventions based on a firm's efforts to recombine knowledge (i.e., knowledge recombinant intensity) and the scope of knowledge that is recombined (i.e., knowledge recombinant diversity), shown in Figure 1.

2.2. Information technology use and knowledge recombination

We propose that a firm's use of IT can accelerate the dissemination of internal knowledge and facilitate the assimilation of external knowledge by enabling efficient research communication and collaboration. IT use can increase the efficiency of communication and facilitate the exchange of scientific knowledge among inventors in a firm's dispersed R&D teams, who may otherwise have no effective means of communication (Forman & van Zeebroeck, 2012). Moreover, firms' IT use can also effectively store, retrieve and disseminate the knowledge if they are equipped with a strong "organizational memory" by IT investment (Tippins & Sohi, 2003). With the use of IT, digitized internal knowledge can be not only communicated in a formal and bidirectional way among inventors but also transferred in an informal and unidirectional search manner. IT use can also enable a firm to assimilate external knowledge in collaboration with researchers from other firms in R&D collaboration (Dong & Netten, 2017; Dong & Yang, 2015; Estrada & Dong, 2019). A greater amount of knowledge from internal and external sources offers more knowledge components and recombinant opportunities, thereby supporting more intensive recombinant efforts of a firm. Therefore, we propose the following hypothesis.

H1: A firm's IT use has a positive effect on its knowledge recombinant intensity.

In the innovation literature, it is apparent that a more interactive and open innovation model is required to collect various sources of knowledge components for recombination (Fleming, 2001; Kogut & Zander, 1992). IT can be used to gather not only more knowledge but also more diverse knowledge from various internal and external sources (Dong & Wu, 2015; Nambisan, 2003). Aside from enabling more intensive recombinant efforts, IT use broadens the search for internal and external knowledge to recombine across a wide range of domains. For example, IT use allows a firm's inventors to use email, instant messaging and collaborative tools, which enhance the richness of their communication and the exchange of knowledge from a variety of research areas (Daft, Lengel, & Trevino, 1987). IT use also aids the accumulation and retrieval of diverse knowledge from a firm's internal inventors and external partners and allows firms to efficiently store and retrieve different sources of knowledge across domains.

IT use helps build a common language platform to create a common form of communication among inventors with different backgrounds so that they can integrate their specialized knowledge in different domains. For example, Malhotra, Majchrzak, Carman, and Lott (2001) found that an aerospace manufacturer used computer-mediated collaboration to enable its team members to exchange a variety of domain-specific knowledge with external team participants in the search for innovation. The use of standardized IT interfaces can also serve as "boundary objects", allowing firms to share different domain-specific knowledge in an effective manner (Malhotra, Gosain, & El Sawy, 2007), which increases a focal firm's use of diverse knowledge from different domains in the recombination. Therefore, we propose the following hypothesis.

H2: A firm's IT use has a positive effect on its knowledge recombinant diversity.

By comparing these two effects, we further propose that the effect of IT use on knowledge recombinant intensity is stronger than the effect of IT use on knowledge recombinant diversity. IT use allows a firm to recombine internal and external knowledge components from and across different domains. While such recombinant efforts supported by IT use always lead to higher knowledge recombinant intensity, only the resultant knowledge recombination across different domains contributes to knowledge recombinant diversity. The innovation literature has documented that knowledge recombination across domains is much more difficult to achieve than knowledge recombination within the same domain (Fleming, 2001). Given a certain amount of knowledge inputs from IT use, the success rate of cross-domain recombination will be much lower than that of within-domain recombination, making the marginal effect of IT use greater for knowledge recombinant intensity than for knowledge recombinant diversity. Based on this reasoning, we propose the following hypothesis.

H3: The positive impact of IT use on knowledge recombinant intensity is stronger than the positive impact of IT use on knowledge recombinant diversity.

2.3. The mediating role of knowledge recombination process

With regard to innovation outcomes, prior studies have documented a direct effect of firms' IT use on innovation outcomes as either increasing the quantity of patent inventions (e.g., Gómez et al., 2017; Joshi et al., 2010; Saldanha et al., 2017; Xue et al., 2012) or improving the quality of patent inventions (e.g., Kleis et al., 2012; Ravichandran et al., 2017). Based on these findings, we further propose that IT use can support knowledge recombinant intensity, which, in turn, generates a high quantity of patent inventions. It has long been recognized that innovation outcomes result from firms' persistent efforts invested in knowledge recombination (Fleming, 2001; Nelson & Winter, 1982). With the IT enablement of intensive recombinant efforts, firms can produce more patent inventions by identifying fruitful recombinant opportunities from available knowledge components (Almeida, 1996). Prior recombinant efforts also allow a firm to gain familiarity with more knowledge components that are relevant to specific tasks in the innovation process. Such intensive efforts can accumulate recombinant experience and domain-specific task advice, leading to firm-specific heuristics (that is, processes for identifying valuable knowledge components and combining them within an architecture that is particularly suitable for a firm), which can considerably promote the productivity of the innovation process (Henderson & Clark, 1990; Wang et al., 2016). Thus, the benefits of IT use for patent quantity are likely to be channelled by a firm's knowledge recombinant intensity.

Furthermore, IT use can support knowledge recombinant intensity, which, in turn, increases patent quality breadth and depth. Greater knowledge recombinant intensity means more extensive efforts to recombine the selective knowledge components for current tasks in the innovation process (Hall, Jaffe, & Trajtenberg, 2001; Valentini, 2012). With the IT enablement of intensive recombinant efforts, firms are also likely to produce a higher quality of patent inventions by identifying and selecting the most compatible and valuable knowledge components in recombination, leading to more useful and impactful patent inventions. Such impactful patent inventions are often manifested by both high patent quality breadth (i.e., impact on future inventions across more domains) and patent quality depth (i.e., impact on a greater number of future inventions). Therefore, the benefits of IT use for patent quality breadth and depth are also likely to be channelled by a firm's knowledge recombinant intensity. Overall, we have the following hypothesis.

H4: Knowledge recombinant intensity mediates the positive impacts of IT use on a) patent quantity, b) patent quality breadth, and c) patent quality depth.

As mentioned earlier, prior studies have separately shown the positive impacts of IT use on patent quantity and quality (e.g., Gómez et al., 2017; Joshi et al., 2010; Kleis et al., 2012; Ravichandran et al., 2017; Saldanha et al., 2017; Xue et al., 2012). We further propose that IT use can support knowledge recombinant diversity, which, in turn, generates a high quantity of patent inventions. Greater knowledge recombinant diversity translates to greater leaps into new knowledge territories, leading to more recombinant opportunities from a variety of different domains for recombining non-redundant knowledge components. On average, this diversity results in a greater number of patents (Carnabuci & Operti, 2013; Harrison & Sullivan, 2011, Rivette & Kline, 1999). Thus, the benefits of IT use for patent quantity are likely to be channelled by a firm's knowledge recombinant diversity.

Furthermore, IT use can support knowledge recombinant diversity, which, in turn, generates significant patent quality breadth and depth. Greater knowledge recombinant diversity means that, on average, patent inventions result from recombining the knowledge components from a variety of domains. With the IT enablement of cross-domain recombination, a firm can integrate apparently distinct knowledge components, resulting in inventions that are more impactful for developing a wide range of applications in different areas (Fleming, 2001; Hargadon & Sutton, 1997). Thus, the patent quality breadth is likely to be high when knowledge recombinant diversity is high. Moreover, the most valuable innovation opportunities often arise from bridging different knowledge domains, which leads to breakthrough inventions that are extremely impactful to the future trajectory of developing numerous inventions (Dong, McCarthy, & Schoenmakers, 2017; Yan, Dong, & Faems, 2019). Thus, patent quality depth is also likely to be high when knowledge recombinant diversity is high. Therefore, the benefits of IT use for patent quality breadth and depth are likely to be channelled by a firm's knowledge recombinant diversity. Overall, we have the following hypothesis.

H5: Knowledge recombinant diversity mediates the positive impacts of IT use on a) patent quantity, b) patent quality breadth, and c) patent quality depth.

3. Methodology

3.1. Data

We adopt a longitudinal design and construct a large-scale panel dataset from multiple archival sources to test our hypotheses. First, we obtained IT data from the Harte Hanks' Computer Intelligence (CI) database between 2001 and 2003 (e.g., Dong & Yang, 2015; Tian & Xu, 2015; Xue et al., 2012). The CI database provides detailed information about firms' use of various technologies at the company site level. We aggregated site-level IT data to the firm level. Though various IT applications have been developed in recent years, our measure of IT use is focused on IT infrastructure, including computing, networking and storage equipment, which is always important for supporting IT applications and still accounts for a large proportion of IT investment today (Aral & Weill, 2007; Bharadwaj, 2000). Furthermore, our choice of 2001–2003 data can facilitate a comparison with recent IS studies based on data from the same time span (e.g., Tian & Xu, 2015).

Second, we merged IT data with financial data from the Standard and Poor's Compustat database for the U.S. public firms. We used firms' ticker symbols to merge IT data from the CI database with the Compustat database. The authors also undertook a follow-up search of company history (e.g., parent company, mergers and acquisitions, and so on) for the unmatched firms based on Marquis' Who's Who database, Thomson Reuters' Securities Data Company (SDC) Platinum database, the Lexis Nexis database, company websites, Wikipedia profiles and Google news. A second round of data merging for unmatched firms was then carried out based on a better understanding of unmatched firms' history to obtain a large sample.

Finally, we collected patent and citation data from the National Bureau for Economic Research (NBER) Patent Citations database (Hall et al., 2001). This database has been widely used in past research to measure innovation outcomes (e.g., Kleis et al., 2012; Xue et al., 2012). It contains detailed, patent-level information from the U.S. Patent and Trademark Office (USPTO) for 3,209,376 patents and 23,650,891 citations of patents granted between 1976 and 2006. Since our unit of analysis is the firm, we aggregated the information on patents and their citations to the assignee level, then to the firm level (a firm may have multiple patent assignees), and then merged it with the Compustat database based on the match file provided by NBER linking firms' GVKEYs to patent assignees' names. The patent application year was used in the data merging process because a patent may be granted later than its application year (Hall et al., 2001).

After merging the above three data sources and eliminating the observations with missing data, we obtained a final sample of 4059 firm-year observations for 1622 unique firms between 2001 and 2003. Compared to prior studies (e.g., Joshi et al., 2010; Kleis et al., 2012; Ravichandran et al., 2017; Saldanha et al., 2017; Xue et al., 2012), our sample has a much larger size that allows better generalizability of findings. Appendix A provides an overview of sample distribution by industry, where our dataset covers firms from 66 SIC two-digit industries.

3.2. Measures

IT use: We follow prior studies to measure IT use as the count of servers, personal computers (PCs), local area network (LAN) nodes, and the storage capacity in gigabytes used by a firm, scaled by the number of employees (e.g., Gómez et al., 2017; Joshi et al., 2010; Tambe, Hitt, & Brynjolfsson, 2012; Zhu & Kraemer, 2002). Such a measure of IT use per capita reflects the degree to which IT infrastructure is intensively used by employees in a firm. While this measure is focused on IT infrastructure, the use of IT applications is arguably correlated with the use of IT infrastructure. For example, a firm's extensive use of social media applications requires considerable investment in computers, network connections, and data storage. We normalize this variable by taking the natural logarithm to reduce the skewness of its distribution.[1]

Knowledge recombinant intensity: From the knowledge recombination perspective, a patent can be viewed as a recombination of existing knowledge from prior patents (Gruber et al., 2012; Nerkar &

Paruchuri, 2005), and patent citations have therefore been widely used to indicate the knowledge components used in recombination (e.g., Carnabuci & Operti, 2013; Fleming, 2001; Gruber et al., 2012; Katila & Ahuja, 2002; Nerkar & Paruchuri, 2005; Phene et al., 2006; Rosenkopf & Nerkar, 2001; Wang et al., 2016). Therefore, we measure knowledge recombinant intensity based on the average number of *backward* citations that a firm made *per patent* in a specific year. The rationale for this measure is that the more knowledge elements that are recombined by a firm to create a new patent, the more intensive its knowledge recombinant efforts are for that patent. Since this measure is a count variable, we take the natural logarithm to reduce the skewness of its distribution (Kleis et al., 2012; Xue et al., 2012).

Knowledge recombinant diversity: We rely on the widely used originality measure to capture knowledge recombinant diversity (e.g., Hall et al., 2001; Valentini, 2012). USPTO has created a highly elaborate patent classification system indicating knowledge domains consisting of 417 three-digit patent classes (Hall et al., 2001). The originality measure is a Herfindahl-style measure identifying the diversity of patent classes from which each patent cites other patents,[2] where patent classes define different knowledge domains (Fleming, 2001; Rosenkopf & Nerkar, 2001). To construct this measure, we first ascertained the three-digit USPTO patent classes for all utility patents granted between 1976 and 2006 and then calculated the originality measure for each patent. Specifically, we calculated this measure as $1 - \sum_{j=1}^{n} c_{ij}^2$, where c_{ij} represents the proportion of the citations *made* by a focal firm's patent i to the patents in patent class j. We then took the average for all patents granted to a firm in a specific year to capture knowledge recombinant diversity *per patent*. This measure indicates the average degree to which a firm recombines knowledge elements from different domains to create a new patent.

Patent quantity: The quantity of patent inventions has been broadly used as the measure of innovation outcomes in digital innovation research (e.g., Joshi et al., 2010; Saldanha et al., 2017; Xue et al., 2012). Following prior studies, we measure patent quantity as the total number of patents granted to a firm in a specific year. Since this measure is a count variable, we take the natural logarithm to reduce the skewness of its distribution (Kleis et al., 2012; Xue et al., 2012).

Patent quality: We use the widely used generality measure to capture patent quality breadth (e.g., Hall et al., 2001; Valentini, 2012), which is a Herfindahl-style measure indicating the breadth of each patent's impact on subsequent patent inventions across different knowledge domains.[3] We ascertained three-digit USPTO patent classes for all utility patents granted between 1976 and 2006, and first calculated the measure for each patent. This measure was calculated as $1 - \sum_{j=1}^{n} r_{ij}^2$, where r_{ij} indicates the proportion of the citations *received* by a focal firm's patent i from the patents in patent class j. We then took the average for all patents granted to a firm in a specific year to capture patent quality breadth *per patent*. If a firm's patents, on average, have a widespread impact on subsequent patent inventions in a wide range of different domains, we consider its patent quality breadth to be large (Rosenkopf & Nerkar, 2001; Valentini, 2012).

We measure patent quality depth as the average number of *forward* citations received by a firm per patent in a specific year (Kleis et al., 2012; Ravichandran et al., 2017). The greater this measure is, the more citations a firm's patents on average receive from subsequent patent inventions, that is, the greater is the patent quality depth *per patent*. With a modest correlation of 0.566, patent quality breadth and depth do not necessarily covary with each other (e.g., a patent may receive many citations in a single domain, leading to low patent quality breadth and high patent quality depth).

3.3. Control variables

Several potential confounding factors are controlled for in this study. First, we control for *IT labour* as the percentage of employees who are IT personnel recruited by a firm (e.g., Tambe & Hitt, 2012; Tambe et al., 2012). Second, while our theory focuses on the influence of IT investment on patent quantity and quality, we control for *R&D intensity* as another important resource for the innovation process in the empirical analysis (Kleis et al., 2012). We measure R&D intensity by a firm's total R&D spending scaled by total sales (Greve, 2003; Kleis et al., 2012). Third, diversification of product lines, including related and unrelated diversification, is often correlated with a firm's knowledge access and sources. Therefore, we control for *related diversification* by using an entropy measure of the extent to which a firm operates across multiple four-digit SIC codes that are within a two-digit SIC code, and control for *unrelated diversification* by using an entropy measure capturing the degree of operations across two-digit SIC codes (Dewan, Michael, & Min, 1998). Formally, let N be the number of four-digit SIC industries that a firm operates in, indexed by i, which, in turn, aggregates into M two-digit industry groups, indexed by j. N_j is the number of different industries in group j, s_i is the share of industry i in total firm sales, s^j is the share of group j in total firm sales, and s_i^j is the sales to each industry i divided by sales to group j. We calculated related diversification as $\sum_{j=1}^{M} \sum_{i=1}^{N_j} s_i^j \ln \frac{s^j}{s_i^j}$, and unrelated diversification as $\sum_{j=1}^{M} s^j \ln \frac{1}{s^j}$. Fourth, we control for *capital intensity* as total assets divided by total sales, which is used as a proxy of other organizational resources (Im, Grover, & Teng, 2013). Fifth, we also control for *financial leverage* as long-term debt divided by total assets, which potentially influences firm risk preference and innovation (Dong & Yang, 2015). Sixth, we control for *firm growth* as the mean percentage of sales growth for the previous year and current year, which may be correlated with a firm's market opportunities and the need for innovation (Kobelsky, Richardson, Smith, & Zmud, 2008). Seventh, *firm size* is controlled by the natural logarithm of total sales. Finally, we include 65 two-digit SIC *industry dummies* and 2 *year dummies* to control for the fixed effects of industry and time. Tables 1 and 2 report descriptive statistics and correlations of our variables.

4. Results

We use ordinary least squares (OLS) regression to test our hypotheses. A one-year time lag is used between IT use and the dependent variables to avoid reverse causality and consider the lagged effects of IT. To test H1 and H2, knowledge recombinant intensity and knowledge recombinant diversity in the subsequent year are used as the dependent variables, respectively. Table 3 reports the regression results for testing H1 and H2. We sequentially estimate the control model and then add IT use. We find that IT use has a statistically significant and positive effect on knowledge recombinant intensity. Thus, H1 is supported. Furthermore, we find that IT use also has a statistically significant and positive effect on knowledge recombinant diversity. Thus, H2 is also supported.

To test H3, we need to compare the effect of IT use on knowledge recombinant intensity and the effect of IT use on knowledge recombinant diversity. Since the OLS coefficients are derived from two separate models, we cannot directly compare them. For comparison of regression coefficients from multiple models, a Chow test is often used (Chow, 1960). However, a Chow test compares coefficients from models that are estimated based on different datasets. Our models are estimated based on the same data, making the Chow test not appropriate. We, therefore, conduct a seemingly unrelated regression (SUR) to estimate our two models simultaneously. When the predictors of the two models are the same, SUR results are equivalent to OLS results (Zellner, 1962) while allowing us to compare the coefficients from one estimation. We find that the effect of IT use on knowledge recombinant intensity is significantly larger than the effect of IT use on knowledge recombinant diversity (Chi-square = 28.280, $p < 0.001$). Thus, H3 is supported.

To test H4 and H5, we use two alternative approaches. First, we follow Baron and Kenny (1986) approach and use patent quantity, patent quality breadth and patent quality depth as the dependent variables, respectively. Table 4 reports the regression results. After estimating the control model, we add IT use and find that IT use has statistically significant and positive effects on patent quantity, patent quality breadth, and patent quality depth. We then add knowledge recombinant intensity and knowledge recombinant diversity to the model. Both knowledge recombinant intensity and knowledge recombinant diversity have statistically significant and positive effects on patent quantity, patent quality breadth, and patent quality depth. In the meantime, the effects of IT use become much smaller for patent quantity and become insignificant for patent quality breadth and depth. These results jointly suggest that knowledge recombinant intensity and diversity *partially* mediate the effect of IT use on patent quantity and *fully* mediate the effect of IT use on patent quality breadth and depth. Thus, H4 and H5 are supported.

Second, we conduct a Sobel test to examine the significance of the mediating effects of knowledge recombinant intensity and diversity (Sobel, 1982). We find that knowledge recombinant intensity significantly mediates the positive relationships between IT use and patent quantity ($z = 2.698$, $p < 0.01$), between IT use and patent quality breadth ($z = 2.424$, $p < 0.05$), and between

Table 1. Descriptive Statistics.

	Mean	SD	Min	Max
Patent quantity (logged)	0.633	1.363	0	7.810
Patent quality breadth (Herfindahl)	0.058	0.192	0	1
Patent quality depth (logged)	0.089	0.271	0	3
Knowledge recombinant intensity (logged)	4.543	10.655	0	134.727
Knowledge recombinant diversity (Herfindahl)	0.162	0.276	0	1
IT use (ratio)	1.193	0.728	0	6.785
IT labor (ratio)	0.048	0.089	0	1.745
R&D intensity (ratio)	0.020	0.045	0	0.545
Related diversification (entropy)	0.104	0.236	0	1.472
Unrelated diversification (entropy)	0.189	0.315	0	2.089
Capital intensity (ratio)	13.534	73.966	0.038	2809.999
Financial leverage (ratio)	0.220	0.204	0	2.095
Firm growth (percentage)	0.043	0.321	−0.996	12.617
Firm size (thousands of USD, logged)	5.685	1.712	1.099	11.537

Table 2. Correlations.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Patent quantity													
(2) Patent quality breadth	**0.619**												
(3) Patent quality depth	**0.566**	**0.566**											
(4) Knowledge recombinant intensity	**0.576**	**0.375**	**0.414**										
(5) Knowledge recombinant diversity	**0.671**	**0.464**	**0.454**	**0.653**									
(6) IT use	**0.045**	−0.011	0.003	0.024	0.013								
(7) IT labor	**−0.084**	**−0.067**	**−0.060**	**−0.069**	**−0.092**	**0.293**							
(8) R&D intensity	**0.359**	**0.219**	**0.246**	**0.204**	**0.295**	**0.114**	−0.022						
(9) Related diversification	**0.108**	**0.055**	**0.037**	**0.107**	**0.122**	−0.004	**−0.055**	**−0.033**					
(10) Unrelated diversification	**0.150**	**0.105**	**0.069**	**0.085**	**0.109**	−0.010	**−0.033**	**−0.085**	**0.042**				
(11) Capital intensity	−0.017	−0.011	−0.005	−0.021	**−0.041**	**0.053**	**0.033**	−0.021	−0.022	**−0.036**			
(12) Financial leverage	**−0.064**	−0.026	−0.039	−0.029	**−0.040**	**−0.063**	**−0.064**	**−0.138**	−0.016	**0.068**	**0.042**		
(13) Firm growth	**−0.049**	**−0.039**	−0.056	−0.019	−0.023	−0.012	0.006	**−0.078**	−0.008	−0.007	0.022	−0.010	
(14) Firm size	**0.345**	**0.211**	**0.150**	**0.206**	**0.262**	**−0.150**	**−0.123**	**−0.039**	**0.231**	**0.229**	**−0.159**	**0.058**	−0.011

Notes: Correlations in bold are significant with $p < 0.05$.

Table 3. OLS Regression Results for Knowledge Recombinant Intensity and Diversity.

	DV: Knowledge recombinant intensity		DV: Knowledge recombinant diversity	
	(1)	(2)	(3)	(4)
IT use		1.271**		0.032***
		(0.417)		(0.007)
IT labor	1.464	−0.799	0.053	−0.004
	(1.342)	(1.291)	(0.037)	(0.037)
R&D intensity	22.021***	20.167***	0.875***	0.829***
	(6.534)	(6.483)	(0.183)	(0.181)
Related diversification	3.075**	2.945**	0.077***	0.074***
	(1.173)	(1.139)	(0.022)	(0.022)
Unrelated diversification	1.464	1.409	0.042*	0.040*
	(0.752)	(0.746)	(0.018)	(0.018)
Capital intensity	0.006*	0.006*	0.0001*	0.0001*
	(0.003)	(0.002)	(0.0001)	(0.0001)
Financial leverage	−1.341	−1.313	−0.031	−0.030
	(1.069)	(1.058)	(0.029)	(0.028)
Firm growth	0.556	0.620	0.025	0.026*
	(0.359)	(0.364)	(0.013)	(0.013)
Firm size	1.275***	1.355***	0.040***	0.042***
	(0.171)	(0.166)	(0.003)	(0.003)
Constant	−8.294***	−10.028***	−0.264***	−0.397***
	(1.268)	(1.248)	(0.037)	(0.035)
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
R^2	0.200	0.206	0.335	0.340
Adj. R^2	0.185	0.190	0.322	0.327
F	13.260***	13.550***	26.700***	26.960***

Notes: $n = 4059$. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Clustered robust standard errors are in parentheses. 65 industry dummies and 2 year dummies are not tabulated. Dependent variables are knowledge recombinant intensity and knowledge recombinant diversity in the subsequent year.

IT use and patent quality depth ($z = 2.603$, $p < 0.01$). We also find that knowledge recombinant diversity significantly mediates the positive relationships between IT use and patent quantity ($z = 4.260$, $p < 0.001$), between IT use and patent quality breadth ($z = 4.084$, $p < 0.001$), and between IT use and patent quality depth ($z = 3.908$, $p < 0.001$). Again, H3 and H4 are supported.

The OLS results should be interpreted as association rather than causation. Therefore, we further use the Granger causality approach to examine causal relationships underlying our model (Granger, 1980). In Table 5, we regress IT use in the subsequent year on knowledge recombinant intensity, knowledge recombinant diversity, patent quantity, patent quality breadth, and patent quality depth, while controlling for prior IT use and other control variables. We find that none of these variables, except patent quality breadth, has a statistically significant effect on subsequent IT use. Patent quality breadth demonstrates a statistically significant and negative effect on subsequent IT use, which is unlikely to drive the positive relationship between IT use and subsequent patent quality breadth that we observed in hypothesis testing. Thus, we conclude that our results are not driven by reverse causality. Table 6 provides a summary of our results for hypothesis testing.

Table 4. OLS Regression Results for Patent Quantity and Quality.

	DV: Patent quantity			DV: Patent quality breadth			DV: Patent quality depth		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Knowledge recombinant intensity			0.029***			0.002***			0.005***
			(0.005)			(0.001)			(0.001)
Knowledge recombinant diversity			1.702***			0.200***			0.226***
			(0.145)			(0.022)			(0.030)
IT use		0.231***	0.141***		0.014**	0.005		0.023***	0.009
		(0.038)	(0.034)		(0.004)	(0.004)		(0.007)	(0.005)
IT labor	0.417*	0.005	0.035	0.025	0.0002	0.003	0.077*	0.036	0.041
	(0.212)	(0.201)	(0.163)	(0.021)	(0.022)	(0.020)	(0.038)	(0.035)	(0.032)
R&D intensity	6.797***	6.460***	4.470***	0.569***	0.549***	0.340***	0.878***	0.845***	0.551***
	(1.114)	(1.084)	(0.812)	(0.120)	(0.119)	(0.094)	(0.192)	(0.192)	(0.167)
Related diversification	0.186	0.162	−0.048	0.008	0.007	−0.014	0.011	0.009	−0.024
	(0.129)	(0.125)	(0.108)	(0.016)	(0.016)	(0.014)	(0.020)	(0.020)	(0.016)
Unrelated diversification	0.382***	0.372***	0.263***	0.034**	0.034**	0.022*	0.039*	0.038*	0.022
	(0.103)	(0.102)	(0.080)	(0.012)	(0.012)	(0.011)	(0.017)	(0.017)	(0.014)
Capital intensity	0.001*	0.001	0.001*	0.0001**	0.0001**	0.0001**	0.0001*	0.0002*	0.0001*
	(0.001)	(0.001)	(0.0004)	(0.0001)	(0.0001)	(0.0004)	(0.0001)	(0.0001)	(0.0001)
Financial leverage	−0.297*	−0.291*	−0.202*	−0.010	−0.010	−0.001	−0.019	−0.019	−0.005
	(0.126)	(0.123)	(0.086)	(0.017)	(0.017)	(0.014)	(0.024)	(0.024)	(0.020)
Firm growth	0.025	0.037	−0.026	0.001	0.002	−0.005	−0.009	−0.008	−0.017
	(0.037)	(0.037)	(0.035)	(0.006)	(0.006)	(0.006)	(0.009)	(0.009)	(0.010)
Firm size	0.310***	0.324***	0.214***	0.026***	0.027***	0.016***	0.029***	0.031***	0.014***
	(0.023)	(0.024)	(0.020)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Constant	−2.009***	−2.325***	−1.514***	−0.199***	−0.218***	−0.135***	−0.262***	−0.293***	−0.171***
	(0.264)	(0.249)	(0.191)	(0.029)	(0.028)	(0.021)	(0.043)	(0.042)	(0.033)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.403	0.414	0.595	0.186	0.188	0.282	0.211	0.214	0.320
Adj. R^2	0.391	0.403	0.587	0.171	0.173	0.268	0.196	0.199	0.307
F	35.790***	37.020***	74.880***	12.140***	12.140***	20.000***	14.170***	14.220***	24.040***

Notes: $n = 4059$. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Clustered robust standard errors are in parentheses. 65 industry dummies and 2 year dummies are not tabulated. Dependent variables are patent quantity, patent quality breadth and patent quality depth in the subsequent year.

Table 5. OLS Regression Results for IT Use.

	(1)	(2)	(3)
Patent quantity			0.020
			(0.011)
Patent quality breadth			−0.086*
			(0.043)
Patent quality depth			0.023
			(0.019)
Knowledge recombinant intensity		−0.001	−0.002
		(0.001)	(0.001)
Knowledge recombinant diversity		0.043	0.026
		(0.036)	(0.039)
Prior IT use	0.769***	0.769***	0.765***
	(0.021)	(0.021)	(0.021)
IT labor	0.301**	0.301**	0.297**
	(0.114)	(0.114)	(0.114)
R&D intensity	0.509	0.508	0.373
	(0.289)	(0.292)	(0.299)
Related diversification	−0.004	−0.003	−0.004
	(0.029)	(0.029)	(0.029)
Unrelated diversification	−0.004	−0.004	−0.008
	(0.024)	(0.024)	(0.024)
Capital intensity	−0.0005**	−0.0005**	−0.0005**
	(0.0001)	(0.0001)	(0.0002)
Financial leverage	−0.038	−0.040	−0.038
	(0.041)	(0.041)	(0.041)
Firm growth	0.015	0.016	0.017
	(0.020)	(0.020)	(0.020)
Firm size	0.005	0.005	0.001
	(0.006)	(0.006)	(0.006)
Constant	−0.936***	−0.937***	−0.911***
	(0.059)	(0.059)	(0.060)
Industry dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
R^2	0.635	0.636	0.636
Adj. R^2	0.628	0.628	0.628
F	84.480***	82.350***	79.520***

Notes: $n = 3763$. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Clustered robust standard errors are in parentheses. 65 industry dummies and 2 year dummies are not tabulated. Dependent variable is IT use in the subsequent year.

Table 6. Summary of Results.

Hypothesis	Results
H1: A firm's IT use has a positive effect on its knowledge recombinant intensity.	Supported
H2: A firm's IT use has a positive effect on its knowledge recombinant diversity.	Supported
H3: The positive impact of IT use on knowledge recombinant intensity is stronger than the positive impact of IT use on knowledge recombinant diversity.	Supported
H4: Knowledge recombinant intensity mediates the positive impacts of IT use on a) patent quantity, b) patent quality breadth, and c) patent quality depth.	Supported
H5: Knowledge recombinant diversity mediates the positive impacts of IT use on a) patent quantity, b) patent quality breadth, and c) patent quality depth.	Supported

5. Discussion and conclusion

5.1. Implications and contributions

Our study provides several important theoretical implications and contributes to the digital innovation literature. First, we open up the black box of the innovation process through which IT use influences patent inventions by proposing the missing link of knowledge recombination. Prior studies documented some controversial findings about IT use and innovation outcomes; most studies found a positive link between IT use and innovation outcomes (e.g., Gómez et al., 2017; Joshi et al., 2010; Ravichandran et al., 2017; Xue et al., 2012), while others reported a non-significant effect (e.g., Aral & Weill, 2007) or a weak relationship (e.g., Kleis et al., 2012). Thus, there is a need to develop a deeper understanding of the underlying mechanisms through which IT use influences innovation outcomes, which helps explain why IT use may not always be associated with superior innovation outcomes if firms fail to develop these mechanisms (e.g., Barua, Konana, Whinston, & Yin, 2004; Rai, Patnayakuni, & Patnayakuni, 2006).

We theorize the innovation process from a knowledge recombination perspective and identify two critical channels through which IT use can influence patent inventions. Our study shows that the intensity of a firm's recombinant efforts (i.e., knowledge recombinant intensity) and the diversity of knowledge components that are recombined (i.e., knowledge recombinant diversity) are key factors channelling the impacts of IT use on patent inventions. Interestingly, the impact of IT use on knowledge recombinant intensity is stronger than the impact of IT use on knowledge recombinant diversity. This finding sheds some light on the nature of IT's role in the innovation process, which seems more functional for facilitating firms' recombinant efforts, and to a lesser extent, supporting distant knowledge search and "boundary-spanning" recombination. More importantly, we find that IT use increases both knowledge recombinant intensity and knowledge recombinant diversity, which, in turn, lead to a greater amount and higher quality of patent inventions. This new insight deepens our understanding with regard to how IT use contributes to innovation outcomes in the form of patent inventions and why some firms may not benefit from IT use for innovation if IT is not used to facilitate recombinant efforts and broaden the recombinant scope in the innovation process.

Second, we examine the nuanced impacts of IT use through knowledge recombinant intensity and diversity on patent inventions in terms of both quantity and quality. Our study enriches the digital innovation literature by conceptualizing patent quality in terms of breadth, indicating the degree to which a firm's patents have widespread citations from subsequent patents across different domains (e.g., Hall et al., 2001; Valentini, 2012), and in terms of depth, measured by the average number of citations that a firm's patents receive from subsequent patents (e.g., Kleis et al., 2012; Ravichandran et al., 2017). Our results show that knowledge recombinant intensity and diversity *partially* mediate the effect of IT use on patent quantity and *fully* mediate the effect of IT use on patent quality breadth and depth. Thus, a firm's efforts and scope of knowledge recombination are more critical for channelling the impact of IT use on innovation quality relative to innovation quantity. While IT use can also directly affect patent quantity, its impact on patent quality, in terms of both breadth and depth, must be channelled by knowledge recombinant efforts and scope. To improve patent quality via the use of IT, firms must use IT to support intensive recombinant efforts with knowledge components from a variety of domains in the innovation process.

Some important managerial implications can also be derived from this study. Our research provides new insight into the impact of IT use on the innovation process leading to patent inventions and reveals how knowledge recombinant intensity and diversity channel the impacts of IT use on patent quantity and quality. In practice, it is likely that some firms have invested substantially in IT but still fail to generate more or improve the quality of patent inventions. Our findings indicate that firms should use IT to support their efforts of recombining diverse knowledge, which will improve the quantity and quality of patent inventions. In particular, the use of IT can substantially empower firms' efforts in knowledge recombination. For firms that already own many patents but aim to improve their patent quality, IT must be used to support recombinant efforts and scope – which will fully carry over the benefits of IT use to improve patent quality – rather than other innovation initiatives and mechanisms.

5.2. Limitations and future research

This study has limitations and points to new directions for future research. First, we explore the mechanisms underlying the innovation process between IT use and patent inventions from a knowledge recombination perspective only. Although this perspective is particularly suitable for explaining the innovation process with respect to patent inventions, it is not the only theoretical lens for understanding the innovation process leading to other innovation outcomes, such as new products and services and new business models. While beyond the scope of this study, future study may explore whether the innovation process enabled by IT use differs from that of other forms of innovation.

Second, we use backward citations to measure knowledge recombination and forward citations to measure patent quality, which cannot fully capture the novelty of recombination and innovation. Though patent citations are objective and accurate due to patent laws and are available over time on a large scale, future study may collect survey data with alternative measurements to replicate our results. Our measure of IT use includes firms' usage of several basic technologies, including servers, PCs, networks, and storage capacity, that have great importance at all times. While this measure is consistent with prior studies, caution is needed when generalizing our findings to more recent years, as these basic technologies are rapidly advancing, and new applications based on these technologies are constantly emerging.[4] For instance, in light of the emergence of big data, firms' storage capacity has been quickly extended, with greater importance for benefiting innovation

(Dong & Yang, 2019). Future study can gather more recent data for an updated portfolio of technologies.

Last but not least, our sample includes a large number of firms across industries and years, but they are all publicly listed, large U.S. companies. Caution should thus be taken when generalizing our findings to other organizational or national contexts. Future study may collect data from small and medium enterprises in other countries to examine our findings. Moreover, due to data availability, our panel covers a limited time period between 2001 and 2003. Future study can gather data from recent years to examine our findings.

5.3. Conclusion

In this study, we draw on the knowledge recombination perspective to develop a model that characterizes the innovation process between IT use and innovation outcomes – in the form of patent inventions – based on a firm's knowledge recombinant intensity and diversity. Using a large-scale panel dataset, we find empirical evidence corroborating our model. Our results indicate that IT use has a stronger impact on knowledge recombinant intensity relative to knowledge recombinant diversity. The impact of IT use on patent quantity is partially mediated while the impact of IT use on patent quality is fully mediated by knowledge recombinant intensity and diversity. This study takes an initial step to open up the black box of the innovation process between IT use and innovation outcomes and provides a process-oriented approach for future research to deepen our understanding of how digital innovation emerges in firms.

Notes

1. We add one to all variables before log-transformation to handle zero values.
2. Hall et al. (2001) suggested that Herfindahl-style measures may be biased due to the count nature of patent data and provided approaches to correct the bias. We followed Hall et al. (2001) to calculate adjusted originality measure for knowledge recombinant diversity and found it is highly correlated with the unadjusted originality measure (r = 0.975), suggesting that the unadjusted originality measure is not much biased. Appendix B shows consistent results for adjusted Herfindahl-style measures that are used in this study.
3. We also followed Hall et al. (2001) to calculate adjusted generality measure for patent quality breadth and found it is highly correlated with the unadjusted generality measure (r = 0.990), suggesting that the unadjusted generality measure is not much biased. Appendix B shows consistent results for adjusted Herfindahl-style measures that are used in this study.
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References

Almeida, P. (1996). Knowledge sourcing by foreign multinationals: Patent citation analysis in the U.S. semiconductor industry. *Strategic Management Journal*, *17*(S2), 155–165.

Aral, S., & Weill, P. (2007). IT assets, organizational capabilities, and firm performance: How resource allocations and organizational differences explain performance variation. *Organization Science*, *18*(5), 763–780.

Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic and statistical considerations. *Journal of Personality and Social Psychology*, *51*(6), 1173–1182.

Barua, A., Konana, P., Whinston, A., & Yin, F. (2004). An empirical investigation of net-enabled business value. *MIS Quarterly*, *28*(4), 585–620.

Bharadwaj, A. (2000). A resource-based perspective on information technology capability and firm performance: An empirical investigation. *MIS Quarterly*, *24*(1), 169–196.

Carnabuci, G., & Operti, E. (2013). Where do firms' recombinant capabilities come from? intra-organizational networks, knowledge, and firms' ability to innovate through technological recombination. *Strategic Management Journal*, *34*(13), 1591–1613.

Chow, G. C. (1960). Tests of Equality between sets of coefficients in two linear regressions. *Econometrica*, *28*(3), 591–605.

Daft, R. L., Lengel, R. H., & Trevino, L. K. (1987). Message equivocality, media selection, and manager performance: Implications for information systems. *MIS Quarterly*, *11*(3), 355–366.

Devaraj, S., & Kohli, R. (2003). Performance Impacts of information technology: Is actual usage the missing link? *Management Science*, *49*(3), 273–289.

Dewan, S., Michael, S. C., & Min, C. K. (1998). Firm characteristics and investments in information technology: Scale and scope effects. *Information Systems Research*, *9*(3), 219–232.

Dong, J. Q., McCarthy, K. J., & Schoenmakers, W. W. M. E. (2017). How central is too central? Organizing interorganizational collaboration networks for breakthrough innovation. *Journal of Product Innovation Management*, *34*(4), 526–542.

Dong, J. Q., & Netten, J. (2017). Information technology and external search in the open innovation age: New

findings from Germany. *Technological Forecasting and Social Change*, *120*(1), 223–231.
Dong, J. Q., & Wu, W. (2015). Business value of social media technologies: Evidence from online user innovation communities. *Journal of Strategic Information Systems*, *24*(2), 113–127.
Dong, J. Q., & Yang, C.-H. (2015). Information technology and organizational learning in knowledge alliances and networks: Evidence from U.S. pharmaceutical industry. *Information and Management*, *52*(1), 111–122.
Dong, J. Q., & Yang, C.-H. (2019). Business value of big data analytics: A systems-theoretic approach and empirical test. *Information and Management*. In Press.
Estrada, I., & Dong, J. Q. (2019). Learning from experience? Technological investments and the impact of coopetition experience on firm profitability. *Long Range Planning*. In Press.
Fleming, L. (2001). Recombinant uncertainty in technological search. *Management Science*, *47*(1), 117–132.
Forman, C., & van Zeebroeck, N. (2012). Form wires to partners: How the internet has fostered R&D collaborations within firms. *Management Science*, *58*(8), 1549–1568.
Gómez, J., Salazar, I., & Vargas, P. (2017). Does information technology improve open innovation performance? An Examination of Manufacturers in Spain. *Information Systems Research*, *28*(3), 661–675.
Granger, C. W. J. (1980). Testing for Causality: A Personal Viewpoint. *Journal of Economic Dynamics and Control*, *2* (1), 329–352.
Greve, H. R. (2003). A behavioral theory of R&D expenditures and Innovations: Evidence form shipbuilding. *Academy of Management Journal*, *46*(6), 685–702.
Gruber, M., Harhoff, D., & Hoisl, K. (2012). Knowledge recombination across technological boundaries: Scientists vs. engineers. *Management Science*, *59*(4), 837–851.
Hall, B. H., Jaffe, A. B., & Trajtenberg, M. (2001). "The NBER patent citation data file: Lessons, insights and methodological tools," *NBER Working Paper* 8498, National Bureau of Economic Research, Cambridge, MA, pp. 1–74.
Hargadon, A., & Sutton, R. I. (1997). Technology brokering and innovation in a product development firm. *Administrative Science Quarterly*, *42*(4), 718–749.
Harrison, S. S., & Sullivan, P. H. (2011). *Edison in the boardroom revisited: how leading companies realize value from their intellectual property*. Hoboken, NJ: John Wiley & Sons.
Henderson, R. M., & Clark, K. B. (1990). Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Administrative Science Quarterly*, *35*(9), 9–30.
Im, K. S., Grover, V., & Teng, J. T. C. (2013). Do large firms become smaller by using information technology? *Information Systems Research*, *24*(2), 470–491.
Joshi, K. D., Chi, L., Datta, A., & Han, S. (2010). Changing the competitive landscape: Continuous Innovation through IT-based knowledge capabilities. *Information Systems Research*, *21*(3), 472–495.
Katila, R., & Ahuja, G. (2002). Something old, something new: A Longitudinal study of search behavior and new product introduction. *Academy of Management Journal*, *45*(8), 1183–1194.
Kleis, L., Chwelos, P., Ramirez, R. V., & Cockburn, I. (2012). Information Technology and Intangible Output: The Impact of IT Investment on Innovation Productivity. *Information Systems Research*, *23*(1), 42–59.
Kobelsky, K. W., Richardson, V. J., Smith, R. E., & Zmud, R. W. (2008). Determinants and *consequences* of firm information technology budgets. *Accounting Review*, *83*(4), 957–995.
Kogut, B., & Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science*, *7*(5), 502–518.
Malhotra, A., Gosain, S., & El Sawy, O. A. (2007). Leveraging standard electronic business interfaces to enable adaptive supply chain partnerships. *Information Systems Research*, *18*(3), 260–279.
Malhotra, A., Majchrzak, A., Carman, R., & Lott, V. (2001). Radical innovation without collaboration: A case study at boeing-rocketdyne. *MIS Quarterly*, *25*(2), 229–249.
Nambisan, S. (2003). Information systems as a reference discipline for new product development. *MIS Quarterly*, *27*(1), 1–18.
Nambisan, S., Lyytinen, K., Majchrzak, A., & Song, M. (2017). Digital innovation management: Reinventing innovation management research in a digital world. *MIS Quarterly*, *41*(1), 223–238.
Nelson, R. R., & Winter, S. G. (1982). *An evolutionary theory of economic change*. Cambridge, MA: Belknap Press/Harvard University Press.
Nerkar, A., & Paruchuri, S. (2005). Evolution of R&D capabilities: The role of knowledge networks within a firm. *Management Science*, *51*(5), 771–786.
Phene, A., Fladmoe-Lindquist, K., & Marsh, L. (2006). Breakthrough innovations in the U.S. biotechnology industry: The . *Strategic Management Journal*, *27*(4), 369–388.
Rai, A., Patnayakuni, R., & Patnayakuni, N. (2006). Firm performance impacts of digitally enabled supply chain integration capabilities. *MIS Quarterly*, *30*(2), 225–246.
Ravichandran, T., Han, S., & Mithas, S. (2017). Mitigating diminishing returns to R&D: The role of information technology in innovation. *Information Systems Research*, *28*(4), 812–827.
Rivette, K., & Kline, D. (1999). *Rembrandts in the attic: Unlocking the hidden value of patents*. Cambridge, MA: Harvard Business School Press.
Rosenkopf, L., & Nerkar, A. (2001). Beyond local search: Boundary-spanning, exploration, and impact in the optical disc industry. *Strategic Management Journal*, *22*(4), 287–306.
Saldanha, T. J. V., Mithas, S., & Krishnan, M. S. (2017). Leveraging customer involvement for fueling innovation: The role of relational and analytical information processing capabilities. *MIS Quarterly*, *41*(1), 267–286.
Sobel, M. E. (1982). Asymptotic intervals for indirect effects in structural equations models. In S. Leinhart (Ed.), *Sociological methodology* (pp. 290–312). Jossey-Bass, San Francisco: CA.
Tambe, P., & Hitt, L. M. (2012). The productivity of information technology investments: New evidence from it labor data. *Information Systems Research*, *23*(:3), 599–617.
Tambe, P., Hitt, L. M., & Brynjolfsson, E. (2012). The extroverted firm: How external information practices affect innovation and productivity. *Management Science*, *58*(5), 843–859.
Tian, F., & Xu, S. X. (2015). How do enterprise resource planning systems affect firm risk? Post-implementation impact. *MIS Quarterly*, *39*(1), 39–60.
Tippins, M. J., & Sohi, R. S. (2003). IT competency and firm performance: Is organizational learning a missing link? *Strategic Management Journal*, *24*(8), 745–761.
Valentini, G. (2012). Measuring the effect of M&A on patenting quantity and quality. *Strategic Management Journal*, *33*(3), 336–346.

Wang, H., Choi, J., Wan, G., & Dong, J. Q. (2016). Slack resources and the rent-generating potential of firm-specific knowledge. *Journal of Management*, *42*(2), 500–523.

Xue, L., Ray, G., & Sambamurthy, V. (2012). Efficiency or innovation: How do industry environments moderate the effects of firms' IT asset portfolio? *MIS Quarterly*, *36*(2), 509–528.

Yan, Y., Dong, J. Q., & Faems, D. (2019). Not every coopetitor is the same: The impact of technological, market and geographical overlap with coopetitors on firms' breakthrough inventions. *Long Range Planning*, In Press.

Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). The new organizing logic of digital innovation: An agenda for information systems research. *Information Systems Research*, *21*(4), 724–735.

Zellner, A. (1962). An efficient method of estimating seemingly unrelated regression equations and tests for aggregation bias. *Journal of the American Statistical Association*, *57*(298), 348–368.

Zhu, K., & Kraemer, K. L. (2002). E-Commerce metrics for net-enhanced organizations: Assessing the value of E-commerce to firm performance in the manufacturing sector. *Information Systems Research*, *13*(3), 275–295.

Appendix A: Sample distribution by industry

SIC two-digit code	Description	Observations	Percentage (%)
01	Agricultural production – crops	11	0.27
10	Metal mining	12	0.30
12	Coal mining	5	0.12
13	Oil and gas extraction	58	1.43
14	Mining and quarrying of nonmetallic minerals, except fuels	7	0.17
15	Construction – general contractors and operative builders	30	0.74
16	Heavy construction, except building construction, contractor	12	0.30
17	Construction – special trade contractors	12	0.30
20	Food and kindred products	138	3.40
21	Tobacco products	9	0.22
22	Textile mill products	48	1.18
23	Apparel, finished products from fabrics and similar materials	58	1.43
24	Lumber and wood products, except furniture	40	0.99
25	Furniture and fixtures	57	1.40
26	Paper and allied products	75	1.85
27	Printing, publishing and allied industries	81	2.00
28	Chemicals and allied products	245	6.04
29	Petroleum refining and related industries	40	0.99
30	Rubber and miscellaneous plastic products	63	1.55
31	Leather and leather products	20	0.49
32	Stone, clay, glass, and concrete products	33	0.81
33	Primary metal industries	107	2.64
34	Fabricated metal products	92	2.27
35	Industrial and commercial machinery and computer equipment	288	7.10
36	Electronic and other electrical equipment and components	329	8.11
37	Transportation equipment	152	3.74
38	Measuring, photographic, medical, and optical goods, and clocks	177	4.36
39	Miscellaneous manufacturing industries	40	0.99
40	Railroad transportation	14	0.34
41	Local and suburban transit, and interurban highway transportation	6	0.15
42	Motor freight transportation	40	0.99
44	Water transportation	4	0.10
45	Transportation by air	41	1.01
46	Pipelines, except natural gas	2	0.05
47	Transportation services	12	0.30
48	Communications	50	1.23
49	Electric, gas and sanitary services	211	5.20
50	Wholesale trade – durable goods	134	3.30
51	Wholesale trade – nondurable goods	46	1.13
52	Building materials, hardware, garden supplies and mobile homes	15	0.37
53	General merchandise stores	52	1.28
54	Food stores	35	0.86
55	Automotive dealers and gasoline service stations	31	0.76
56	Apparel and accessory stores	79	1.95
57	Home furniture, furnishings and equipment stores	27	0.67
58	Eating and drinking places	70	1.72
59	Miscellaneous retail	115	2.83
60	Depository institutions	3	0.07
61	Non-depository credit institutions	18	0.44
62	Security and commodity brokers, dealers, exchanges and services	56	1.38
63	Insurance carriers	124	3.05
64	Insurance agents, brokers and services	34	0.84
65	Real estate	16	0.39
67	Holding and other investment offices	9	0.22
70	Hotels, rooming houses, camps, and other lodging places	17	0.42
72	Personal services	17	0.42
73	Business services	311	7.66
75	Automotive repair, services and parking	12	0.30
76	Miscellaneous repair services	3	0.07
78	Motion pictures	5	0.12
79	Amusement and recreation services	44	1.08
80	Health services	64	1.58

(*Continued*)

(Continued).

SIC two-digit code	Description	Observations	Percentage (%)
82	Educational services	10	0.25
83	Social services	12	0.30
87	Engineering, accounting, research, and management services	64	1.58
99	Non-classifiable establishments	17	0.42
Total		4059	100

Appendix B: OLS results for adjusted herfindahl-style measures

	(1)	(2)	(3)	(4)
	Knowledge recombinant diversity (adj.)	Patent quantity	Patent quality breadth (adj.)	Patent quality depth
Knowledge recombinant intensity		0.035*** (0.005)	0.004*** (0.001)	0.006*** (0.001)
Knowledge recombinant diversity (adj.)		1.251*** (0.145)	0.309*** (0.041)	0.165*** (0.032)
IT use	0.025*** (0.007)	0.155*** (0.035)	0.008 (0.008)	0.011* (0.005)
IT labor	−0.013 (0.036)	0.050 (0.171)	0.001 (0.036)	0.043 (0.032)
R&D intensity	0.602*** (0.158)	4.999*** (0.878)	0.694*** (0.183)	0.622*** (0.173)
Related diversification	0.074*** (0.022)	−0.033 (0.111)	−0.031*** (0.025)	−0.022 (0.016)
Unrelated diversification	0.040* (0.017)	0.272*** (0.083)	0.039* (0.020)	0.023 (0.014)
Capital intensity	0.0001* (0.00004)	0.001* (0.0004)	0.0002** (0.0001)	0.0001* (0.0001)
Financial leverage	−0.027 (0.026)	−0.211* (0.092)	−0.003 (0.026)	−0.006 (0.020)
Firm growth	0.020 (0.011)	−0.010 (0.033)	−0.004 (0.011)	−0.015 (0.010)
Firm size	0.034*** (0.003)	0.234*** (0.021)	0.030*** (0.004)	0.017*** (0.003)
Constant	−0.249*** (0.031)	−1.662*** (0.205)	−0.246*** (0.038)	−0.191*** (0.035)
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
R^2	0.282	0.569	0.253	0.309
Adj. R^2	0.269	0.561	0.238	0.295
F	20.610***	67.390***	17.250***	22.780***

Notes: n = 4059. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Clustered robust standard errors are in parentheses. 65 industry dummies and 2 year dummies are not tabulated. Dependent variables are knowledge recombinant diversity (adj.), patent quantity, patent quality breadth and patent quality depth in the subsequent year.